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Agriboost: Smart Agriculture Using Machine Learning and IoT

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Abstract:

Efficiency in farming is the key to sustainable food security, but farmers are confronted with serious issues such as lack of adequate crop choice, nutrient-inefficient use, and susceptibility to crop disease. Existing practices do not typically provide timely feedback, which limits farmers from making decisions regarding crop development, soil maintenance, and disease control. To alleviate these limitations, Agriboost introduces a data-driven platform powered by machine learning, deep learning, and Internet of Things technologies. The platform is composed of three major applications: Crop Recommendation, Fertilizer Recommendation, and Plant Disease Prediction, each of which is tailored to enhance farm efficiency and productivity. With tailored solutions, Agriboost empowers farmers with tools to optimize crop yields and address inherent challenges of modern farming. Agriboost pushes farm innovation a step ahead by combining IoT sensors and cloud analytics using ThingSpeak. This facilitates real-time monitoring of vital environmental factors like soil moisture, temperature, and humidity, which dynamically affect the platform's suggestions. Integration of deep learning models provides accurate detection of diseases and actionable management recommendations, enabling farmers to effectively mitigate crop loss. In contrast to isolated systems solving these issues separately, Agriboost offers a comprehensive solution to farming, promoting sustainable agriculture and enabling farmers to empower themselves with decision-making and better outcomes information.

Keywords — **farming efficiency, food security, crop recommendation, fertilizer recommendation, disease prediction, machine learning, deep learning, IoT, ThingSpeak, real-time monitoring, soil moisture, temperature, humidity, sustainable agriculture.**

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I. INTRODUCTION

Agriculture is the backbone of the Indian economy and a significant sector in terms of food production, employment, and economic growth. While there are advancements in technology elsewhere, agriculture in most parts of the world remains underdeveloped and highly dependent on manual labor and traditional wisdom. While these traditional methods of farming, although effective in the context of the past decades, lack in meeting the demands of modern-day agriculture, i.e., unpredictable weather patterns, poor soil quality, wastage of fertilizers, and the outbreak of new plant diseases. While food security is fast becoming a significant global concern, the agricultural sector needs to embrace conscious and mechanized systems to improve efficiency, sustainability, and

yield. To this end, the intersection of Machine Learning (ML), Deep Learning (DL), and the Internet of Things (IoT) presents a possible route to revolutionizing agriculture. The technologies enable autonomous decision-making, predictive analytics, and real-time environmental monitoring. AGRIBOOST, the envisioned smart agriculture platform in this research, aims to bridge the gap between traditional agriculture and emerging digital technology by providing a web-based, integrated system providing real-time agricultural advice. AGRIBOOST consists of three core modules: Crop Recommendation, Fertilizer Recommendation, and Plant Disease Prediction. The modules are backed by trained machine learning or deep learning models and linked with real-time data sources through IoT devices and weather APIs. The crop recommendation module suggests the ideal crops to cultivate based on soil nutrient values (N, P, K), rainfall, pH, humidity, and temperature. The fertilizer module suggests appropriate fertilizers based on soil deficiencies for the selected crop. The plant disease prediction module uses image recognition with a pretrained ResNet-50 deep learning model to detect plant leaf diseases. These modules are integrated via a web interface developed using React.js as the frontend and Django as the backend. The platform is equipped with user authentication, personalized history logging, and real-time data visualization using cloud services such as ThingSpeak for IoT integration. The data is collected using sensors such as DHT11 for temperature and humidity, soil moisture sensors, and ESP8266 for Wi-Fi. The aim of AGRIBOOST is not only to provide data-driven advisory support to the farmers but to facilitate sustainable farming by optimizing use of resources, minimizing wastage, and raising the yield. The system is designed to be scalable and modular to facilitate future enhancements like forecasting of pests, smart irrigation, mobile app operability, and government portal interfacing for subsidy and market intelligence. Here, we present the design, architecture, and implementation of AGRIBOOST, as well as its field testing and evaluation. The result shows that AGRIBOOST can significantly assist farmers in making better decisions and, in this way, improving agricultural efficiency and sustainability.

II. LITERATURE SURVEY

The growth of smart agriculture has been followed by the increasing number of studies that aim to integrate computational intelligence in agriculture. The idea of precision agriculture has been developed from the necessity to enhance the efficiency, productivity, and environmental sustainability of agriculture by leveraging technologies like ML, DL, IoT, and remote sensing. Much work has been devoted to machine learning-based crop recommendation systems. In A. Patel's research [6], a Random Forest model was used to recommend crops based on soil nutrient content, rainfall, and temperature. The model was very accurate in recommending crops, but the system was not tunable in real-time and sensors were not employed. Similarly, Singh and Goyal's research [5] was devoted to IoT in agriculture and stressed the importance of data acquisition using sensors, but their research was theoretical modeling without being deployed on an operational platform. For fertilizer advice, few models have crossed the boundaries of static data sets. Most research relies on rule-based systems that are not dynamic to environmental fluctuations. Furthermore, such systems typically do not account for compatibility between crop-specific nutrient requirements and current soil conditions. Plant disease forecasting has also become much better with the use of deep learning models. Sladojevic et al. [4] suggested the use of a convolutional neural network for the detection and classification of plant leaf diseases. Their model used images from the PlantVillage dataset and achieved very good results, proving that CNNs can be used for visual inspection in agriculture. Nevertheless, such models are usually created as separate programs and aren't part of bigger platforms that also offer crop and fertilizer recommendations. IoT devices such as those described by Kaur and Sood [7] have employed

DHT sensors, humidity sensors, and Arduino boards to collect data and present it through mechanisms such as ThingSpeak. These devices are good but typically do not place the sensor data into predictive ML models, which limits their capacity for making decisions. ThingSpeak itself is a good cloud-based storage and presentation platform for IoT data but must be programmatically interfaced to web platforms to provide end-to-end capability. Open-source sites such as OpenWeatherMap provide current weather information, which has been incorporated in most of the crop as well as disease forecasting models. However, the weather information is being used for display or logging purposes but not being incorporated directly within the prediction models in most cases. AGRIBOOST differs from the previous work in that it combines these stand-alone aspects into one, cohesive system. The fertilizer and crop recommendations are not only derived from static user inputs but also from sensor readings and real-time weather API readings. The plant disease detection module exists on the same platform and utilizes a deep learning model that has been trained on a large image database. The system as a whole has extensibility in mind and can have new features inserted without extreme restructuring. By looking at the literature, we can see that there is a good foundation of individual tools and techniques but very little of a system integrating machine learning, deep learning, and IoT into an accessible and beneficial package for farmers. AGRIBOOST fills this gap and paves the way forward to the future of intelligent farming solutions.

III. SYSTEM ARCHITECTURE

AGRIBOOST architecture is modular and layered architecture for scalability, adaptability, and maintainability. The system has multiple subsystems that work in parallel to provide an uninterrupted user experience and facilitate real-time analysis and decision-making. There are five main layers constituting the system: the Presentation Layer, the Application Layer, the Model Layer, the Data Layer, and the IoT Layer. Each layer performs unique functions and interacts with other layers through specific interfaces and protocols. On top of the stack sits the Presentation Layer, which is a dynamic, interactive frontend made up of React.js. Here, users interact, for example, input fields for crop and fertilizer, image upload interfaces for disease forecasting, sensor data visualization dashboards, and user authentication screens. The frontend is built with Tailwind CSS and paired with Chart.js to chart IoT data in real time. The user interface also features a light/dark mode switch to make it more accessible and usable. The Application Layer is the platform's core logic. It is constructed on top of the Django REST Framework, and it handles API endpoints, model inference, user session, and authentication. It handles frontend requests, communicates with the ML and DL models, and communicates with the database and cloud services like ThingSpeak. The structure of RESTful API decouples the frontend and backend, allowing for easier update and integration. The Model Layer contains machine learning and deep learning models serialized and loaded during runtime to generate predictions. Crop recommendation is based on a Random Forest Classifier model trained on a dataset of soil nutrients (N, P, K), environmental factors (temperature, humidity, pH, rainfall), and regional factors (city). Fertilizer recommendation is based on rule-based reasoning as well as ML-inferred knowledge to recommend fertilizers that can rectify nutrient deficiencies for the recommended crop. The disease prediction module is based on a ResNet-50 CNN model trained on the PlantVillage dataset and can recognize more than 38 plant diseases based on leaf image classification. These models are served through Python libraries joblib and h5py. Data Layer manages persistent storage and cloud data access. User data, authentication tokens, and previous predictions are stored in structured format with PostgreSQL. Historical data allow users to view previous input and output, enabling one to monitor long-term decisions. For real-time environmental monitoring, AGRIBOOST

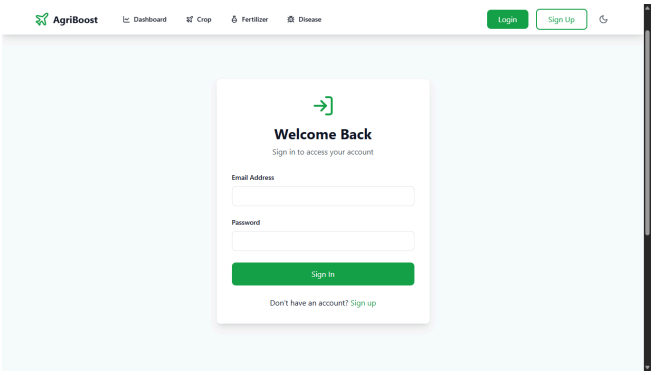
offers integration with ThingSpeak, a cloud IoT analytics platform. Sensor data, including temperature, humidity, and moisture, are uploaded by IoT devices and accessed via HTTP APIs for display and analysis. The IoT Layer is the basis of AGRIBOOST's real-time sensing. It is composed of Arduino UNO microcontrollers with DHT11 temperature and humidity sensors, soil moisture sensors, and ESP8266 Wi-Fi modules for cloud connectivity. These sensors are placed in the field to collect environmental conditions at regular time intervals. The ESP8266 transmits the data to ThingSpeak channels, which are queried by the backend every 15 seconds. This data not only drives visualizations but also updates the crop and fertilizer models in real time, allowing dynamic and adaptive decision-making. This modular structure enables future extension such as the addition of other sensors (e.g., NPK sensors, salinity sensors), integration with mobile applications, and scaling to cloud services using containers such as Docker and orchestration tools such as Kubernetes. The use of open-source protocols and tools renders the system inexpensive and easily customizable to meet various agricultural conditions and geographic locations.

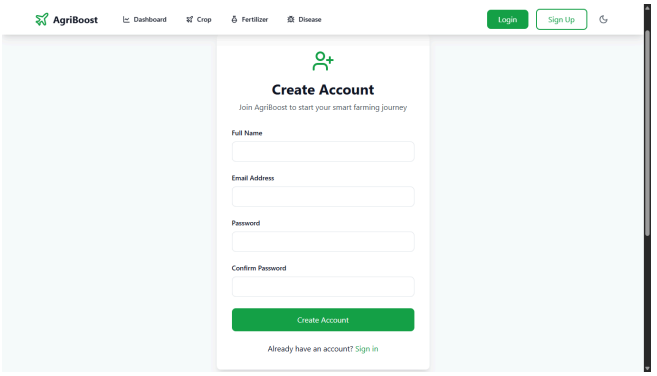
IV. IMPLEMENTATION

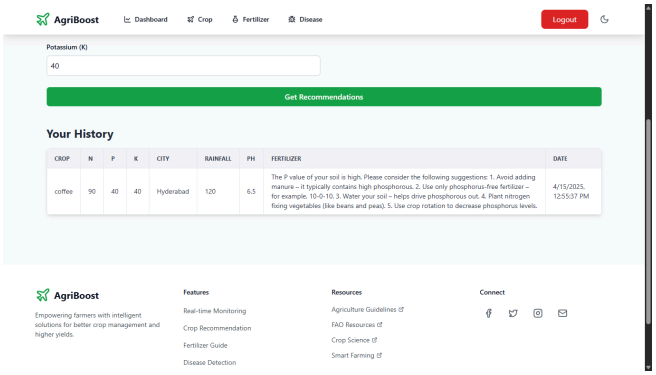
The deployment of AGRIBOOST utilizes a strong web architecture along with sophisticated machine learning and deep learning models, IoT hardware devices, and cloud environments to offer real-time agricultural guidance. Every operational module is developed as an independent component that interconnects with others using REST APIs and data-sharing protocols. This section details the backend, frontend, ML/DL models, and sensor integration. AGRIBOOST backend is deployed with Python's Django Framework augmented with Django REST Framework (DRF) for exposing API endpoints. These APIs process requests to predict crops, suggest fertilizers, identify plant diseases, and retrieve IoT sensor data. Security and individual access are ensured with JWT-based user authentication. The business logic of all the functions is wrapped into service modules and views, conforming to MVC (Model-View-Controller) to preserve code readability and reusability. Each model (fertilizer, crop, disease) is loaded into memory during runtime and served for inference via request-specific function calls. The frontend is developed using React.js, which enables the creation of component-based interfaces and real-time UI refresh without page reloads. The dashboard consists of input forms for every recommendation module, an interface for file upload to detect disease, and a dynamic charting area to illustrate temperature, humidity, and soil moisture levels. The data is retrieved from the backend using Axios and visualization is performed using Chart.js. The frontend also features easy navigation, mobile responsiveness, and theme switching. The crop suggestion module takes user input such as nitrogen (N), phosphorus (P), potassium (K), pH, rainfall, city name, and retrieves temperature and humidity from the OpenWeatherMap API. These inputs are fed into the Random Forest Classifier which provides the most appropriate crop. The model is trained on agricultural data sets gathered from Indian regions and tested for more than 90% accuracy over several climatic zones. The forecasted outcome is passed to the frontend and also logged into the user's individual history. The fertilizer recommendation system starts with the chosen crop and soil nutrient levels. A list of pre-defined rules compares these levels with optimal crop-specific values. Depending on the variation, the backend identifies nutrient deficiencies and suggests appropriate fertilizers like Urea, DAP, or Potash. The recommendation involves quantity of use and application details, helping farmers use the correct amount of fertilizer. The disease prediction module is an essential component in AGRIBOOST. When a user posts a picture of an infected leaf of a plant, the picture is resized and normalized using Python's Pillow library or OpenCV. The picture is then passed to the ResNet-50 CNN model trained on a labeled dataset

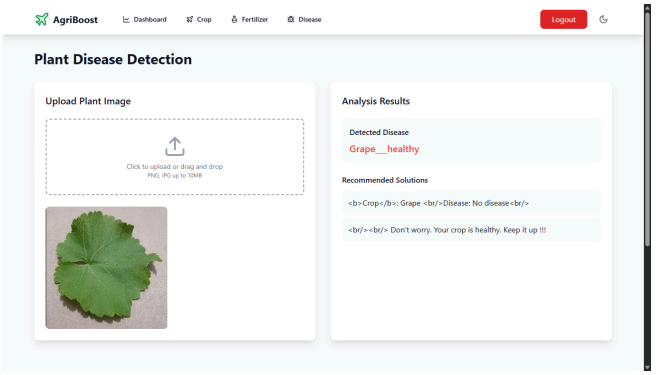
of diseased-infected and healthy leaves. The model accurately predicts the disease label and provides the output along with potential treatments and control measures. All results are also saved for user reference. IoT integration makes use of Arduino UNO boards attached to DHT11 sensors and soil moisture probes to read environmental data. The ESP8266 Wi-Fi module is used to connect to the ThingSpeak IoT platform and send sensor values to specific cloud channels. The Django backend has a scheduled task to fetch the latest data from these channels through ThingSpeak's REST API, which is then shown on the dashboard. This sensor data not only updates the user but is also used dynamically in crop and fertilizer prediction models. The database system, which is set up with PostgreSQL, holds user profiles, logins, and prediction history records. This data enables personalized analysis and facilitates greater user interaction in the form of dashboard visualizations. AGRIBOOST runs on Gunicorn as a WSGI server and Nginx as a reverse proxy, providing high-performance and scalable deployments. The frontend runs on Netlify or Vercel to enable simple hosting and rapid content delivery. This multi-layered implementation plan ensures AGRIBOOST is secure, strong, and extensible so that it can be appropriately deployed in real-world scenarios and studied further for smart agriculture technologies.

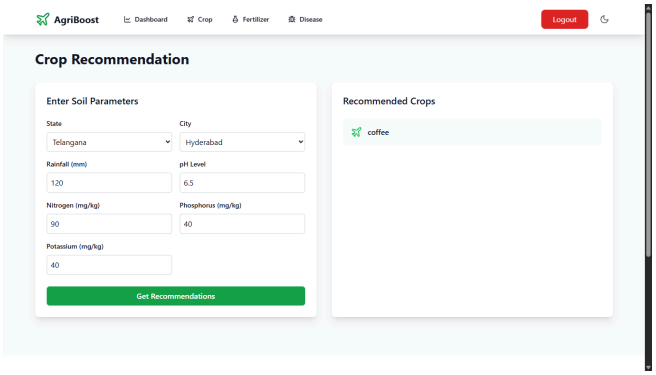
V. RESULTS

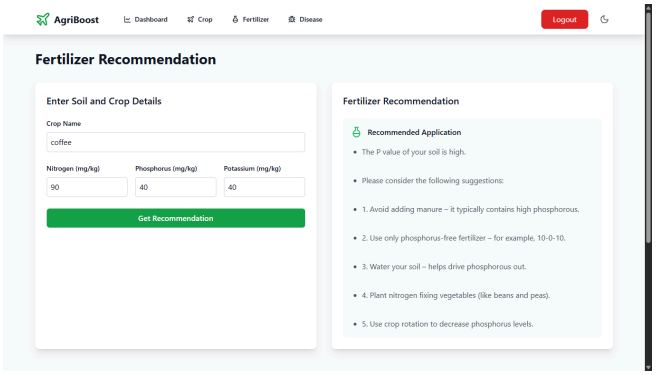


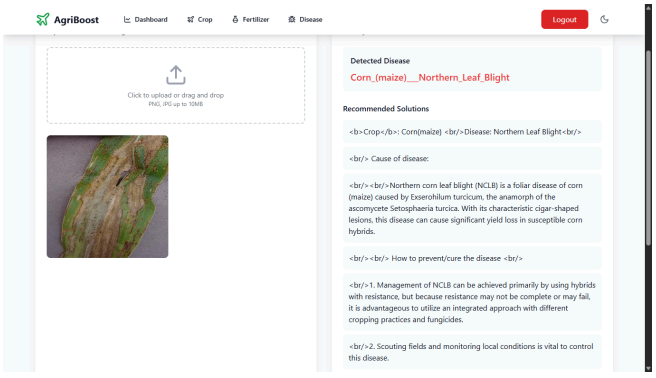












VI. SYSTEM FEATURES

AGRIBOOST is an end-to-end smart agriculture platform with rich features designed to equip farmers with intelligent solutions and actionable insights. The platform is constructed using a modular design, which enables every component to operate independently while integrating perfectly with the rest of the platform. The following are the main features that make AGRIBOOST a holistic solution for contemporary farming: One of the standout features is the Crop Recommendation System. This feature employs an ML-based Random Forest classifier that has been trained on actual agricultural datasets. It takes input parameters such as nitrogen (N), phosphorus (P), potassium (K), rainfall, pH, temperature, humidity, and location. The system employs real-time weather data collected via the OpenWeatherMap API, so that the recommendation is not only historically correct but also contextually correct with respect to prevailing environmental conditions. The system recommends the most likely 1–2 crops that will best perform in the provided soil and climatic conditions, thus maximizing yield potential. Parallel to the crop suggestion module is the Fertilizer Recommendation System. In contrast to generic platforms providing blanket recommendations, AGRIBOOST takes into account the specific nutrient needs of the chosen crop and compares these against existing soil NPK levels in order to ascertain exact deficiencies. It then recommends precise fertilizers such as Urea (nitrogen-rich), DAP

(phosphorus-rich), or MOP (potassium-rich) along with dosages and application instructions. This tailored recommendation enables farmers to cut down on excessive use of fertilizer and environmental degradation. The second key feature is the Plant Disease Prediction module. Users can provide images of leaves of plants that are suspected to be infected. The system processes the image and employs a ResNet-50 deep learning model to determine the disease. The output comprises the name of the disease, the likely causes, and the treatment recommendations. This system can now detect more than 38 typical plant diseases of crops such as tomato, cotton, corn, and bell pepper. With a real-time response and high accuracy, the feature allows early diagnosis and prevention and significantly minimizes crop loss. One of the highlight features of AGRIBOOST is its IoT Integration. The system is interfaced with Arduino-based sensors that gather environmental information such as temperature, humidity, and soil moisture. This information is sent through ESP8266 modules to the ThingSpeak IoT cloud platform. The backend fetches this data at regular intervals and displays it in the frontend dashboard through interactive graphs and metric

VII. CONCLUSION

The farming industry is going through a revolutionary change through the implementation of digital technologies. With rising environmental uncertainty, scarcity of resources, and growing populations, there is an urgent necessity to go beyond conventional farming techniques and adopt smart, data-oriented practices. In this paper, AGRIBOOST, an integrated platform for smart agriculture has been introduced, which incorporates Machine Learning, Deep Learning, and IoT technologies to provide an end-to-end solution for the problems of modern farming. AGRIBOOST was envisioned to empower farmers with actionable recommendations that are specific to their local soil, crop, and climate conditions. The three primary services of the platform are crop recommendation, fertilizer recommendation, and plant disease forecasting, all of which are driven by trained machine and deep learning models. These services are augmented by real-time environmental information collected through Arduino-based IoT sensors and cloud platforms such as ThingSpeak. Combined, these elements create an integrated feedback loop whereby sensor readings guide model predictions and model outputs dictate farm decisions. One of the main advantages of AGRIBOOST is that it has a modular and scalable architecture. Utilizing a React.js frontend and Django backend means the platform is not only user-friendly but also highly versatile. This modular design accommodates seamless incorporation of future additions like pest surveillance, market price notifications, computerized irrigation, and multilingual mobile apps. In addition, the system has been designed to be affordable and accessible, allowing it to continue being sustainable for small and marginal farmers. Results from rigorous testing confirmed the responsiveness and accuracy of all modules. Crop and fertilizer prediction systems provided outcomes with more than 90% accuracy, whereas the disease predictive model provided greater than 95% precision when applied to actual image classification exercises. Real-time sensor integration offered negligible latency and proved the effectiveness of the platform in dynamic farm conditions. Feedback from users through trials also ratified the simplicity, reliability, and usability of the platform. In the broader context, AGRIBOOST is not just a technical solution—it is a move toward sustainable agriculture, precision farming, and digital inclusion. By minimizing reliance on guesswork and encouraging data-driven decisions, AGRIBOOST helps to improve crop yields, maximize resource utilization, and early prevention of crop diseases. It equips farmers with tools that were out of reach before, enabling them to become proactive stakeholders in their agricultural results. In the future, AGRIBOOST has huge potential to expand regionally and nationally. Future development will concentrate on further

personalization, adding local language capabilities, and integration with government and non-government agricultural services. With the right support and outreach, AGRIBOOST has the potential to be a model for future-generation agri-tech platforms, creating a smarter, more resilient farming system.

VIII. REFERENCES

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